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Pricing strategies of low-cost airlines: The Ryanair case study

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ABSTRACT

We analyse the pricing policy adopted by Ryanair, the main low-cost carrier in Europe. Based on a year's fare data for all of Ryanair's European flights, using a family of hyperbolic price functions, the optimal pricing curve for each route is estimated. The analysis shows a positive correlation between the average fare for each route and its length, the frequency of flights operating on that route, and the percentage of fully booked flights. As the share of seats offered by the carrier at the departure and destination airports increases, fares tend to decrease. The correlation of dynamic pricing to route length and the frequency of flights is negative. Conversely, as competition increases discounts on advance fares rise.

1. Introduction

In recent years, the entry of low-cost carriers has totally revolutionised the air passenger transport industry. The low-cost business model was introduced by Southwest in the US at the beginning of the 1970s. However, it was only in the 1990s that the phenomenon spread worldwide. Ryanair was one of the first airlines in Europe to adopt the low-cost model in 1992. Easyjet, Ryanair's main low-cost competitor, was founded in 1995. Although the phenomenon is relatively recent, the stunning results obtained by low-cost carriers urge academics to study the reasons for their success.

The reduction of costs lies at the core of the low-cost business model, which aims to offer lower fares, eliminating some comfort and services that were traditionally guaranteed (hence the definition of "no frills", often employed to refer to low-cost flights). The use of an on-line booking system, the suppression of free in-flight catering, the use of secondary airports connected through a point-to-point network, and the use of homogeneous fleets are only a part of the innovative choices made by low-cost airlines.

Many studies have analysed low-cost businesses, highlighting the keys to lower costs (Alamdari and Fagan, 2005; Doganis, 2006; Franke, 2004), and the role played by entreprership (Cassia et al., 2006). The containment of costs is only one of the reasons for the success of a low-cost carrier. Alertness to "latent demand," characterised by the passenger's willingness to pay elastic prices, which is not the attitude of the so-called "traditional" passenger, is among the key factors.

In the airline business, the maximisation of the profits obtained from each flight is strictly related to the maximisation of revenues, because many of the costs incurred are essentially fixed, at least in the short term. Pricing has always represented an important factor in the carriers' choices, driving the adoption of different strategies by low-cost and full-cost carriers. Full-cost carriers choose price discrimination techniques based on different fare classes, complex systems of discounts with limited access, customer loyalty schemes, and overbooking techniques. Low-cost carriers instead use "dynamic pricing". Because of dynamic pricing, it is now common for people to buy air tickets to European destinations for less than €10.00 (airport taxes excluded).

This paper deals with the pricing policies of low-cost carriers, offering a detailed analysis of Ryanair, the main developer of the low-cost model in Europe. Generally speaking, fares tend to increase until the very last moment before the closing of bookings. If it is assumed that Ryanair aims to maximise its profits, it is to be expected that travellers are prepared to bear higher costs more easily as the date of flight approaches. We aim to identify the competitive and contextual factors that drive the choice of the average fares, and their relative dynamics. In details, our analysis will focus on Ryanair's pricing policies in correlation with the features of its airport network. The results show that the fare policy is clearly innovative relative to traditional pricing strategies, and that the fares are influenced by the competitive economic context in which the route is offered.

2. State of the art

This study refers to two main fields of literature, namely the analysis of the low-cost business model and the study of dynamic pricing techniques. The main point of interest is the extraordinary

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performance of the major low-cost carriers, especially when compared with the trend, and the average profitability, of the air transport industry in general. Researchers have extensively examined the cost-effective policy, which so clearly permeates the low-cost business model. Franke (2004) and Doganis (2006) have focused in particular on the cost benefits that low-cost carriers can derive from their operational choices. Their studies show that there is no single driving element responsible for the competitive advantage. Rather, all the choices made contribute to the production of cost benefits. Gudmundsson (2004), using a longitudinal survey approach, studies factors explaining the success probability of the "new" airlines and finds that productivity and brand image focus are significantly related to financial non-distress, whilst market power (market-share) focus is significantly related to financial distress.

A first mover competitive advantage could explain why the most successful airlines seem to be able to maintain their market leadership in the short and medium term, are the ones that gave rise to the phenomenon, as witnessed by the likes of Southwest in the USA and by Ryanair and Easyjet in Europe. It is clear that, a good low-cost strategy can never be replicated in all its details—and this could account for the carriers that succeeded as well as for those that did not. Alamdari and Fagan's (2005) study quantified the impact of the deviation from the original low-cost business model.

The importance of the different strategic choices made by carriers suggests investigating other elements of the low-cost business model. Revenue analysis is an important element that has been less studied. Indeed, the generation of revenues is one distinctive aspect differentiating low-cost from full-cost airlines policies. Piga and Filippi (2002) have analysed the pricing policies of the low-cost business model in comparison with the pricing strategies of the full-cost airlines. Coherent choices seem to be essential in pricing policies as well. For instance, the widespread use of the Internet for the sale of tickets tends to decrease price dispersion. This phenomenon may in part be attributed to the "efficiency of electronic markets," as defined by Smith (Smith et al., 2000).

The success of the low-cost model is based on a fragile balance between fare levels, load factors and operating costs. The structure of revenues and the determination of prices are nearly as important as the minimisation of costs in the equation of profits. Indeed, an excellent pricing strategy for perishable assets results in a turnover increase, *ceteris paribus*, which can be quantified between 2% and 5%, according to Zhao and Zheng's (2000) study.

The analysis of fare levels and policies aims to understand the key factors in the achievements of low-cost carriers, including the effects of the competitive interaction between carriers (Pels and Rietveld, 2004). The price choices and the ability of the airlines to understand the characteristics of the demand, in either a condition of monopoly or a competitive context, are decisive in the balance of the business model itself. Fare dynamics must be taken into account in a thorough evaluation of market competitiveness, and of the benefits travellers have achieved through deregulation.

This paper analyses the pricing strategies adopted by Ryanair against the characteristics of the context in which it operates, including the degree of competitiveness.

First, the study deals with the demand curve derived from Ryanair's prices. The analysis starts from the microeconomic principles of dynamic pricing. Generally speaking, airlines deal with perishable goods sold in different time steps, with the aim to maximise profits. The offer of seats on a flight can be compared to the sale of "perishable assets" with pre-determined capacity in conditions of negligible marginal costs. The themes investigated by the relevant literature are dynamic pricing and yield management.

Zhao and Zheng (2000) have determined the minimum conditions required for optimal dynamic pricing. Because the price trend is influenced by demand, one part of the literature focuses on optimal pricing policies by using specific functional forms to represent demand and customer benefits. For example, it is quite typical to use an exponential demand curve (Gallego and Van Ryzin, 1994) and a mechanism "of customer arrival" into the market with a probability similar to a Poisson process. The studies mentioned above presuppose a continuous optimal price function. Other studies are more likely to hypothesise the existence of a limited range of prices (Wilson, 1988). The present study adopts a continuous function, because Ryanair offers a wide range of prices.

The study of price dynamics raises interesting questions. Many travellers have probably noticed that prices often tend to increase as the flight date approaches. According to McAfee and te Velde (2006), in the period preceding the flight date, the price trend mainly depends on the trade off between the option of waiting for a potential lower price, and the risk of seats becoming unavailable. In this case, the functional form of the demand curve, together with its adjustment over time, also help to determine a series of minimum prices.

This study analyses the range of actual prices on all of Ryanair's routes. It aims to validate some of the assumptions made in the literature through a thorough study of this wide empirical sample. The estimated demand curve makes it possible to make inferences about the trend of bookings and the curve relating to the fully booked aircraft. Stokey's (1979) studies determined an optimal constant filling curve in a context of monopoly. Similar results can be obtained by using a demand with functional forms belonging to the family of continuous functions presented by Anjos et al. (2005). For such functions, when dealing with goods that are to be sold by a given deadline, it is possible to define and implement the optimal pricing strategy. The reference curves adopted in this study belong to the Anjos family of curves.

The structure of demand, which guides the optimisation choices of the carrier, is influenced by the presence of competitors, and the passengers' opportunities to opt for a substitute service. Classical studies, starting from Borenstein's (1989) analysis, have mainly focused on the airlines' average fare level, showing the undeniable influence exercised by the competitive structure on the fares of full-cost airlines. Such competitive structures are exemplified by a fare premium correlated to the dominance of the hub of reference. Alderighi et al. (2004) have pointed out that full-cost airlines tend to decrease fares on routes also operated by low-cost carriers. The influence of the competitive structure on the pricing strategies of low-cost carriers has been less studied, as far as we know. Pels and Rietveld's (2004) studies have examined the evolution of fares on the London–Paris route; traditional behavioural models do not seem to apply here, given the mixture of direct and indirect competition.

It is not clear whether the presence of other airlines can critically affect the pricing strategies of low-cost carriers. Pitfield (2005) has analysed the routes originating from Nottingham East Midlands airport in 2003, when it was possible to observe low-cost airlines in direct competition. The results showed a weak influence of the competitive structure on prices. The historical pattern of fares offered by each airline seems to play a more important role, as would be expected in a situation of price leadership. In a study examining the London–Berlin and London–Amsterdam routes, Barbot (2005) found that the low-cost and full-cost markets coexist on totally separate levels, so that low-cost carriers compete "only" among themselves, as do full-cost carriers.

The approach we have adopted here focuses on the different behaviours assumed by carriers according to the distinctive characteristics of the routes they operate. We aim to identify the competitive and contextual factors that drive the choice of the average fares, and their relative dynamics.

3. Methodological aspects

The literature on low-cost carriers highlights the important role played by dynamic pricing. It is assumed that once the flights have been scheduled, the marginal costs incurred in relation to the number of passengers are practically null. It follows that the maximisation of profits is strictly dependent on the maximisation of the revenue function. Let the reference unit of time be the single day.[1] Considering T days, the revenue R can be expressed as

$$R = \sum_{i=1}^{T} p_i q_i \tag{1}$$

where p_i is the flight price on the day i of the year, and q_i is the number of seats booked on the same day. The optimal pricing strategy results from the maximisation of the previous expression, under the binding limit of the aircraft's capacity, which can be expressed as

$$\sum_{i=1}^{T} q_i \le Q \tag{2}$$

where Q is the capacity, that is, the total number of seats available on the aircraft.

For the purposes of this study it is assumed that, for the specific route and type of customers availing themselves of low-cost flights, the operator is not a price-taker. We hypothesise that the competitive structure and the level of market and product differentiation enable the operators to modify the price variable. The maximisation problem can be solved through a "lagrangian".

$$L = \sum_{i=1}^{T} p_i q_i + \mu\left(Q - \sum_{i=1}^{T} q_i\right) \tag{3}$$

where μ represents the Kuhn–Tucker's multiplier, which takes into account the aircraft limit of capacity. It follows that

$$\mu\left(Q - \sum_{i=1}^{T} q_i\right) = 0$$

If the limit of capacity is reached, $\mu > 0$; if not, $\mu = 0$. In order to determine the optimal price p_i at the specific time i, the derivative of the expression (3) with respect to p_i must equal zero, thus obtaining

$$\frac{\partial L}{\partial p_i} = q_i + \sum_{j=1}^{T}\left(p_j - \mu\right)\frac{\partial q_j}{\partial p_i} = 0 \quad \text{where } i \in [1, K, T] \tag{4}$$

This expression can be held valid even if the markets on the different days are not "separated." In this case, for example, the fare during one period can modify the quantity of available seats in a successive period, that is, $\partial q_j / \partial p_i \neq 0$ with $i \neq j$. In line with many of the studies analysed in the literature, for the purpose of this study, it is assumed that the markets for the purchase of air tickets are separated in time, that is $\partial q_j / \partial p_i = 0$ with $i \neq j$. A later development of this study will eliminate this hypothesis in order to verify the possible interaction between the demands of the different periods.

Here, expression (4) is simplified in the following optimal conditions:

$$q_i + (p_i - \mu)\frac{\partial q_i}{\partial p_i} = 0 \quad \text{where } i \in [1, K, T] \tag{5}$$

This study considers the functional form of demand as proposed by Anjos et al. (2005), where the demand for air tickets depends on price levels, and on the time interval between the purchase date and the flight date, according to

$$q_i = Ae^{-\alpha \cdot p_i F(i)} \quad \text{where } i \in [1, K, T] \tag{6}$$

where A and α are two constants, and $F(i)$ is a function positively correlated to the time period between the purchase date and the flight date. In this case, the function of demand is subject to an exponential decrease as the advance purchasing time increases.

An advance booking is less useful because people are less sure of their plans far in advance. Given the functional form of the demand in expression (6), it is possible to identify the optimal pricing strategy by substituting the following form for p_i in expression (5).

$$p_i = \mu + \frac{1}{\alpha \cdot F(i)} \tag{7}$$

The multiplier μ can be viewed as the extra charge assigned to the fully booked flights.[2] In the next section, some $F(i)$ forms will be tested on Ryanair's actual prices. The parameters of the price function will be estimated by minimising the quadratic error compared to the actual prices. The underlying assumption is that Ryanair operates by maximising its revenues, and using a demand function similar to function (6). Therefore, the accuracy that may be obtained using the model for the estimation of prices enables assessment of the validity of the forms of the demand curves.

Through the substitution of the optimal price expression (7) in the expression (6), we have

$$q_i = Ae^{-1} \tag{8}$$

Expression (8) implies that, following the application of the optimal price, the expected demand is steady over time. If the quantity sold over a certain time span is greater than the steady expected quantity, the operator may decide to raise the price. Similarly, the operator may decide to reduce the price in order to gain demand when demand is scarce.

In the empirical calculations, two functions are used for the estimation of prices. The first expression is

$$p_i = \mu + \frac{1}{\alpha \cdot (1 + \beta \cdot i)} \tag{9}$$

where i is the number of days between the advance reservation and the flight date. The form of the optimal price is a hyperbola with the price going up as the flight date approaches. This functional form makes it impossible to obtain price reductions as the flight date approaches.

A more complete functional form is

$$p_i = \mu + \frac{1}{\alpha \cdot \left(1 + \beta \cdot i + \gamma \cdot i^2 + \theta\sqrt{i}\right)} \tag{10}$$

In this case, the price may decrease as the departure date approaches. The degree of accuracy of both functional forms will be discussed in the next section.

The hypothesis is that Ryanair has tailored a pricing strategy for specific routes. In other words, it is assumed that Ryanair holds specific values for the parameters in (9) and (10) for each individual route. An estimation of the parameters of the price functions is made for each route using data from the 90-day period before the flight date.

[1] Demand and prices are assumed to be fixed over the single day.

[2] Fully booked flights have no available seats on the day before departure.

4. Sample and descriptive analysis

4.1. Reference data

Our database includes the daily fare for each route[3] operated by Ryanair over the 4 months prior to the flight. The study examined all the flights scheduled by Ryanair from 1st July, 2005, until 30th June, 2006. The database enables (1) a comparison between the fares for the different routes, and (2) tracing the fare variation for each individual route as the flight date approaches.

4.2. Characteristics and evolution of the network operated by Ryanair

Ryanair's network is characterised by a very dynamic and steady expansion. A comparison between the data gathered as of 1st July, 2005, and later on 30th June, 2006, gives a clear picture of the dimensions of the phenomenon: in July, 2005, Ryanair served 95 airports, increasing to 111 one year later; over the same period, routes expanded by 34.4%, reaching the total number of 594 (see Table 1).

Table 1
Variation of the network operated by Ryanair between July 2005, and June 2006.

Variable	7/1/2005	6/30/2006	Δ %
Number of served airports	95	111	16.8
Number of daily flights (average)	650.2	820.7	26.2
Number of routes	442	594	34.4
Percentage of routes with daily flight frequency	70.1%	70.8%	
Percentage of routes with more than a daily flight frequency	23.6%	3.4%	
Percentage of routes with no daily flight frequency	6.3%	25.8%	

Nonetheless, 25 routes that were operated in July 2005 were then cancelled; 6 routes saw their flight frequency halved; and the frequencies of 16 other routes were each decreased by more than 10%. Ryanair operates on many low-frequency routes, 70.8% of the overall network being made up of routes with only one single flight per day. By and large, it may be said that Ryanair serves its routes daily. However, in 2005–2006 this trend changed, as the number of routes with no guaranteed daily flight increased from 14 to 77.

An estimation of Ryanair's ASK[4] (Available Seat Kilometres) distribution is made possible by the information available about the scheduled flights, and the distance between the departure and arrival airports. From a geographical point of view (see Fig. 1), Ryanair's main business focuses on the connection between England, Ireland, and the rest of Europe (44.2% of the routes, and 49% of the flights start at British or Irish airports). The major flow (measured in ASK) is between Italy and England (14.6%) (see Table 2). Apart from the British Isles, the main flow is between Italy and Spain (3.1% of the whole business). The domestic routes play a relatively small role, accounting for less than 5% of the scheduled air traffic, in terms of numbers of both flights and routes. Italy is the only place besides the British Isles in which Ryanair operates domestic routes.

The significant increase in new routes and markets occurred in a surprisingly balanced way. The geographic distribution in 2006 is approximately the same as in 2005, with only a slight decrease in service to the UK (Table 3).

Ryanair's network comprises mainly short-length journeys, with all its routes ranging between 200 km and 2000 km and with a median value of 1040 km (as shown in Fig. 2). The distribution proves symmetrical with respect to the median value, forming a bell-shape histogram with the exception of two peak levels at 450 and 1800 km.

Fig. 3 shows the percentile distribution of ticket prices with respect to advance booking in days. It is understood that prices may vary according to other parameters as well, for example, route specificity. Yet the role played by advance reservation in Ryanair's pricing policy is so significant that average figures also provide important information about Ryanair's pricing strategies. For instance, the figures demonstrate that in 75% of cases (75th percentile in Fig. 3) the price[5] does not exceed €50 for bookings made at least 20 days earlier than the actual date of flight. On the contrary, during the last week prior to the flight all prices increased sharply, with ticket prices exceeding €75 within 3 days of the date of flight in 50% of the cases, and topping €200 in 5% of the cases.

The impression of a steady increase in prices as the date of flight approaches is verified only on average. As a matter of fact, Ryanair makes sure to provide "special offer" periods in which fares reach their lowest. Such periods do not seem to have any particular recurrence in terms of length and time. When restricting the analysis to flights operated on the same route only, it is not possible to mark a specific period for promotions. Indeed, most routes show a slight increase in prices, or at least a steady upward trend similar to most of the percentiles shown in Fig. 3. Fig. 4 shows the average price trend on the Rome Ciampino–London Stansted route (one with high-frequency service), while Fig. 5 shows the exact price on specific dates. Fig. 4 compares two price trends pertaining to two dates, neither of which falls on a holiday (such as a bank holiday or a religious festival). No steady price trend can be observed in either case: over the 90 days leading to the flight date, lower fares are offered as the departure day approaches, but this occurs in the two cases during different periods of time, with different lengths and intensities. If it is assumed that this phenomenon may occur often in Ryanair's pricing policy, it may be inferred that the expectations of the passengers should admit a probability (p) for the price to fall in the following days.

Thanks to the database at our disposal, we were able to investigate the recurrence of special offers in Ryanair's pricing policy. For each individual flight we calculated the percentage of days on which the price offered was lower than any other previous price. Data were gathered per route, and analysed according to the pattern of distribution of the percentages. Fig. 6 shows the distribution by percentiles on the Rome Ciampino–London Stansted route. On this route, 50%[6] of the flights monitored ('50th percentile' in Fig. 6), do not show any downward price trend within 30 days of the date of flight. In the case of 30-day advance bookings, 25% of cases (75th percentile curve) were recorded with at least 6 following days on which prices were lower than the one recorded on the day, whilst 2.5% of cases recorded at least 18 days in a row with lower prices.

The data gathered do not provide information about the actual number of seats booked for each single flight. Conclusions on volumes are drawn in the empirical analysis (Fig. 10). Nevertheless, the data show whether the flights were fully booked in the 24-h period before the scheduled departure date. As a matter of fact, Ryanair makes use of a non-refundable ticket policy and no

[3] At the beginning of July 2005, the total number of routes was 442, while by the beginning of July, 2006, it had risen to 594. The definition of route is to be intended here as directional. Outbound and inbound routes between two airports are thus considered as two different routes.

[4] ASK (Available Seat kilometres) accounts for the number of seats available on a flight multiplied by the route's length (in kilometres).

[5] Unless otherwise stated, the price mentioned throughout this work refers to the "net" fare indicated on Ryanair's website, which excludes other cost categories such as airport taxes, security fees and credit/debit card handling fees.

[6] Referred to 691 out of 1382 flights monitored on the route analysed.

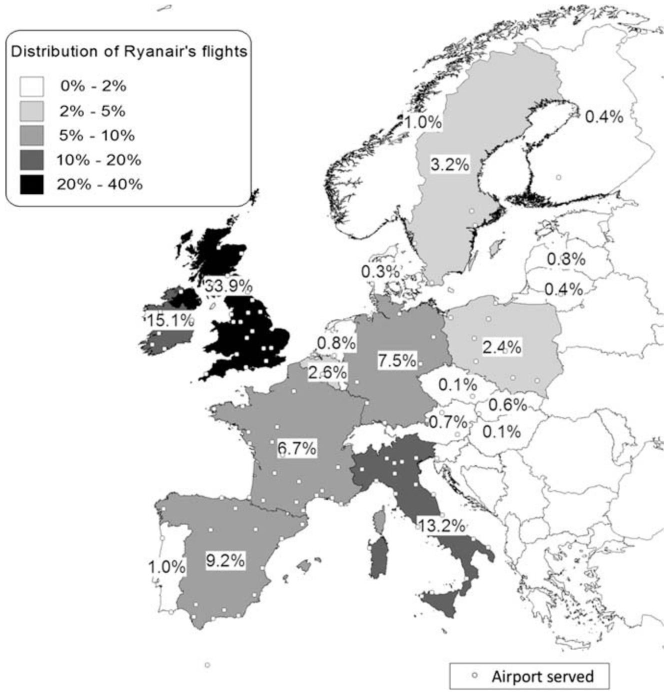

Fig. 1. Distribution of Ryanair's flights and served airports (as of 30th June, 2006).

Table 3
Distribution of Ryanair's flights considering their country of origin and their variation.

	Situation as of 1/7/2005			Situation as of 6/30/2006		
	Routes	Daily flights (average)	Flight share	Routes	Flights (average)	Flight share
AT	5	6.0	0.9%	5	6.0	0.7%
BE	11	16.6	2.6%	16	21.7	2.6%
CZ	1	1.0	0.2%	1	1.0	0.1%
DE	41	50.6	7.8%	48	61.5	7.5%
DK	2	2.7	0.4%	2	2.9	0.3%
ES	52	65.3	10.1%	61	75.1	9.2%
FI	3	3.0	0.5%	3	3.4	0.4%
FR	30	40.1	6.2%	46	55.3	6.7%
HU	–	–	–	1	1.0	0.1%
IE	50	91.8	14.1%	80	123.7	15.0%
IE (domestic)				(2)	(6.0)	(0.7%)
IT	69	94.4	14.5%	78	108.0	13.2%
IT (domestic).	(6)	(10.0)	(1.5%)	(6)	(12.0)	(1.5%)
LT	–	–	–	3	3.0	0.4%
LV	4	4.0	0.6%	6	6.6	0.8%
NL	5	5.7	0.9%	6	6.7	0.8%
NO	5	6.3	1.0%	7	8.3	1.0%
PL	1	1.0	0.2%	18	19.4	2.4%
PT	3	4.0	0.6%	7	8.0	1.0%
SE	17	23.0	3.5%	20	26.0	3.2%
SK	–	–	–	4	5.0	0.6%
UK	143	234.8	36.1%	183	278.1	33.9%
UK (domestic)	(10)	(21.5)	(3.3%)	(14)	(25.4)	(3.1%)
Total	442	650.2	100%	594	820.7	100%

overbooking procedures, which means that when a flight is fully booked the website shows the unavailability of seats. For each individual flight, we calculated the fully booked flight ratio (where fully booked flights are defined for our purposes as those with no available seats in the last 24 h before departure). Fig. 7 shows the distribution of routes according to the fully booked flights ratio. The same period was monitored for all routes and covered all of the months considered in the analysis. The figures highlight the unquestionable ability to fill all seats available on the different routes, with most of Ryanair's routes being declared fully booked 10–20 times out of 100.

5. Empirical analysis

In the empirical analysis, we applied Eq. (9) to estimate the price trends for each individual route. The equation was obtained from an exponential demand function subject to Ryanair's profit maximisation, and showed that, as the date of flight approaches, the price trend tends to resemble a hyperbola driven by parameters α and β, where α indicates the highest price level that may be reached during the last days before the scheduled departure date. The lower α is, the higher the fare will be the day before departure. Parameter β indicates instead a decrease in the fares that is directly proportional to the increase in the number of advance booking days before departure. A low β will show a steady price trend as the number of advance booking days increases. On the contrary, a high β indicates a significantly discounted fare, with respect to the highest fare ever offered, on advance purchases. Finally, parameter μ shows the average surcharge in the cases of flights characteristically fully booked on the day before the scheduled departure.

These parameters were calculated for all routes for which fares dating back to at least three months before the actual date of flight were available. 550 out of the 594 monitored routes have been taken into consideration. The remaining routes had been only recently introduced, were monitored for less than three months, and consequently were not taken into account. The parameter estimates were carried out by minimising the standard error of the predicted fares for each individual route.

Table 2
Main flows between nations operated by Ryanair (as of 30th June, 2006).

Rank	Country pairs	ASK (daily average)	%
1	England - Italy	22,301,303	14.6
2	England - Spain	19,538,299	12.8
3	England - Ireland	11,175,029	7.3
4	England - France	10,620,722	6.9
5	England - Sweden	6,754,428	4.4
6	England - Poland	6,160,721	4.0
7	England - Germany	5,353,365	3.5
8	Ireland- Spain	5,228,941	3.4
9	Italy - Spain	4,796,374	3.1
10	Italy - Germany	4,680,690	3.1

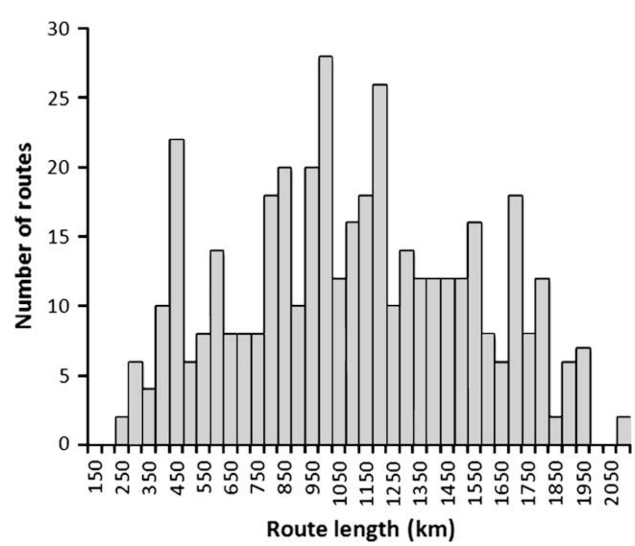

Fig. 2. Route distribution according to route length (as of 1st July, 2006).

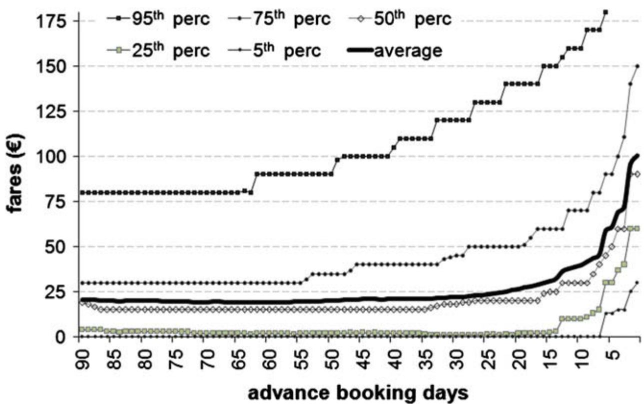

Fig. 3. Fares trend distribution according to advance booking in days.

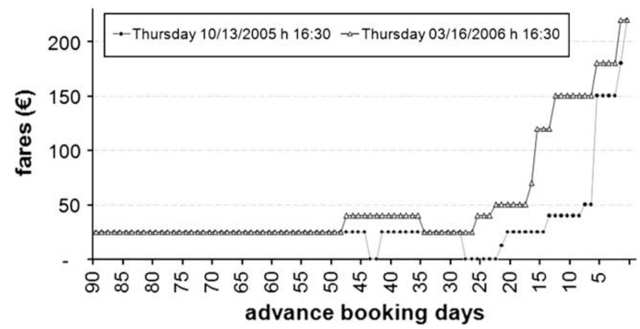

Fig. 5. Prices on the Rome Ciampino–London Stansted route for two specific dates.

The distributions of parameters α and β are shown in Figs. 8 and 9 respectively. The distribution of parameter α shows a higher frequency of routes with parameter α levels around 0.008–0.01, with a maximum average price higher than €100. Parameter β shows the maximum relative frequency with levels slightly above zero; the frequency then decreases as parameter β gets higher. Some routes show a significant higher β level: approximately 50% of the routes register a β level greater than 0.1. In these cases, the purchase of the ticket three months before departure captures a price less than one tenth of the highest fare, which may occur just a few days before the date of flight. The pattern of distribution of parameter β suggests the presence of a cluster of routes characterised by very different dynamic pricing intensity. Yet tests carried out by gathering routes according to the potential presence of competitors do not highlight any significant differences among the clusters.

It is important to note that routes in competition with one another are characterised by specific features, such as a high concentration of service areas with a high GDP (Gross Domestic Product). For this reason, we use regression models to help isolate the effects of each individual variable.

After obtaining the parameters of the optimum price demand curve, it is possible to estimate the average number of daily bookings for each individual route using Eqs. (6) and (8). Fig. 10 shows, for the high-frequency Rome Ciampino–London Stansted route, the average ticket price, the estimated price as calculated with Eq. (9), and on the far right, the estimated number of daily bookings. Thanks to the optimal pricing strategy employed, the number of daily bookings remains steady as the date of flight approaches, in accord with Stokey's (1979) study.

A series of reasons may explain why the estimated and the actual price do not perfectly overlap. First of all, the demand curve cannot be accurately known on a daily basis, and there may be more or fewer bookings than expected on some days. If the actual bookings outnumber expectations, carriers are likely to raise prices in order to deter further bookings, and thus restore the optimum situation. Secondly, operational reasons make Ryanair's fares subject to a discrete rather than constant variation, so that Ryanair's decision to raise its fares results in increases through small increments (generally €5.00). Finally, the parameters were predicted by considering every single flight on every single route, with the aim to provide an extensive amount of data. Nevertheless, it is most likely that both time of the day and day of the week significantly affect pricing strategies. Thanks to the broad database at our disposal, it will be possible with a future development of the analysis to estimate these parameters according to day of the week and time of the day as well.

Following the estimation of the price curve levels and the "flight-filling" function for each route, a regression analysis has been carried out, aiming to study the possible determinants in Ryanair's pricing strategies.

The first regression analyses the "temporal" average price as a dependent variable. This is the arithmetic mean of prices offered on a specific route over a period from three months prior to departure up to the day before. If the flight-filling curve proves optimal, which means that the expected number of average daily bookings is steady over time (Stokey, 1979), the weighted price average against the total number of purchased tickets will equal the temporal average price.

The explanatory variables employed are basically of two kinds: route specific variables, and airports and linked areas specific variables. The route specific variables include route length and daily frequency, percentage of fully booked flights, number of carriers in

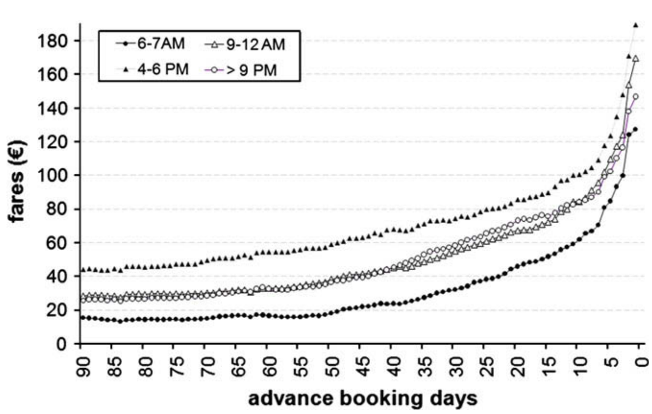

Fig. 4. Average price trend on the Rome Ciampino–London Stansted route according to different daily departure times.

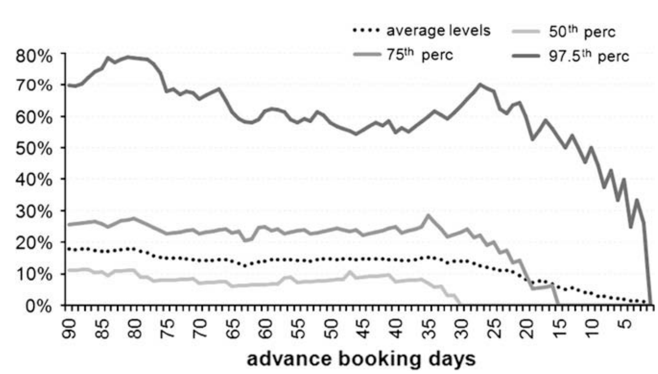

Fig. 6. Percentage of remaining booking days with fares lower than the price applied on the specific date.

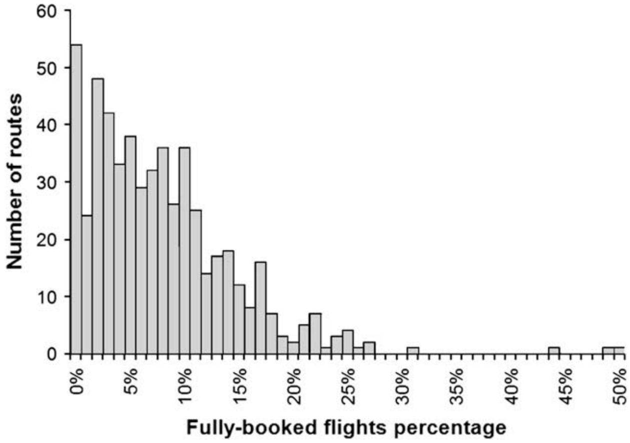

Fig. 7. Distribution of number of routes by fully booked flights percentage.

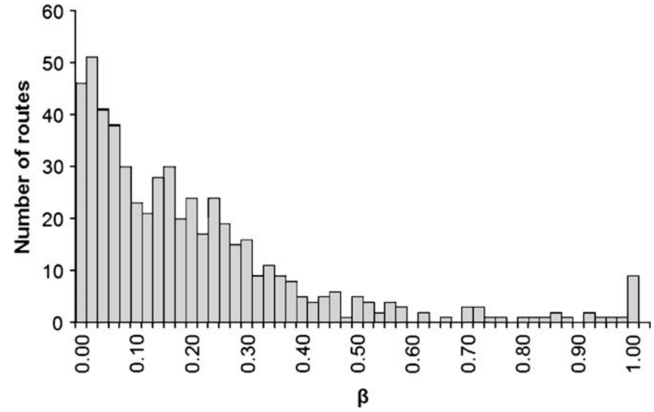

Fig. 9. Distribution of the number of routes according to coefficients β estimated by analysing flight fares.

direct competition on the route, and the overall taxation level to which ticket fares are subject.

Information about the GDP generated by the areas connected and their population density may instead be ranked among the airport and hinterland areas specific variables. In addition, two other variables were put into place in order to reckon Ryanair's importance in the departure and arrival airports: Ryanair ASK/Departure ASK and Ryanair ASK/Destination ASK. Such variables were calculated as the ratio between the total ASK provided by Ryanair on a specific route and the total ASK provided by the departure and destination airports. The results of the regression analysis are shown in Table 4.

The most significant variable affecting the average price for each route is quite predictably the route length. Of similar importance are the variables referring to demand, such as route frequency and percentage of fully booked flights, which show positive coefficients. This confirms that the higher the demand (both in terms of percentage of fully booked flights and daily route frequency), the higher the average prices. Regarding the variables conveying Ryanair's importance in the departure and destination airports, it is interesting that, on average, the greater the importance of Ryanair, for example in its role as main connecting carrier of minor airports, the lower will be the fare. The offer of the discounted fares appears as an incentive to use secondary airports. Moreover, the price correlated positively with the population density of the destination airport. An interpretation of the variables concerning the GDP of the areas connected proves more difficult. The results seem to outline a strategy that fosters demand in high GDP areas. It follows that Ryanair's strategy is keen to attract the latent demand for extra flights typical of the middle class, which is particularly concentrated in high GDP areas. Middle class passengers may be prepared to spend their money on leisure trips, while still being quite sensitive to price changes.

A positive correlation was also found between Ryanair's average price and the overall taxation level on the route, which incidentally could be seen as a proxy variable of the service level provided by the airport. Finally, the presence of competitors does not seem to heavily impact the average price, which confirms once more the complexity and diversity of forms that characterise competitiveness in the air transport industry. As we will see in the following pages, the analysis suggests that it is rather the dynamic pricing that is more likely to be affected by competitiveness.

While it may be said that the average price can provide important information on the single route, it no doubt cannot satisfactorily illustrate how the price might change in the three months before the actual date of flight. In order to study the variables on which dynamic pricing depends, a regression analysis was carried out using parameter β as a dependent variable estimated on the single routes. The results are shown in Table 5.

Length and route frequency are significant variables with negative coefficients. This means that the price trend will acquire steadiness as the route becomes longer, and more frequently travelled. In other words, Ryanair grants fewer discounts on long haul and high-frequency routes, despite advance purchase. A steady price trend may be partly justified when considering that Ryanair needs to cover fuel costs, and will try to do so on advance purchases as well. As regards the discounts offered, it seems that

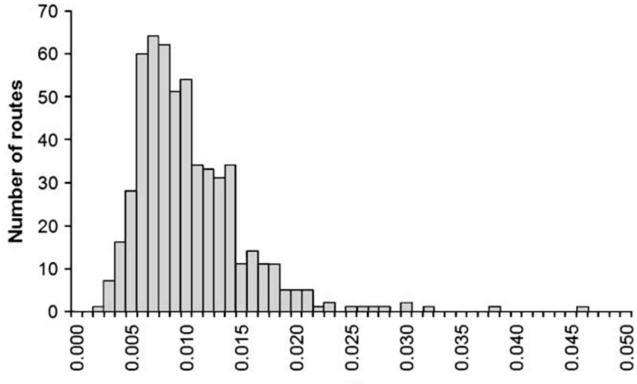

Fig. 8. Distribution of the number of routes according to coefficients α estimated by analysing flight fares.

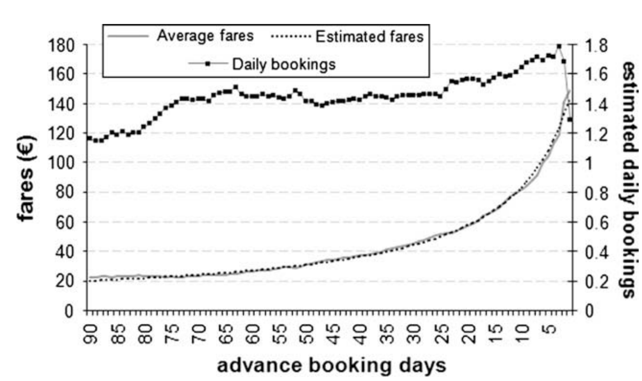

Fig. 10. Comparison between the daily average price and the estimated price on CIA–STN route.

Table 4
Determinants of the average price.

Variable	Coefficient (std error)	Statistic T
Length	0.021 (0.0010)	19.98***
Route frequency	0.100 (0.0496)	2.02***
Ryanair ASK/departure ASK	−9.013 (3.4414)	−2.62***
Ryanair ASK/destination ASK	−8.822 (3.2156)	−2.74***
Overall taxation	0.298 (0.1119)	2.67***
Departure GDP	-0.71×10^{-03} (0.0002)	−2.71***
Destination GDP	-0.46×10^{-03} (0.0002)	−1.74***
% Of fully booked flights	24.116 (7.4912)	3.22***
Departure population density	0.43×10^{-03} (0.0008)	0.52***
Destination population density	0.001 (0.0008)	1.74***
Total number of competitors	0.038 (0.5403)	0.07***
Constant	1.849 (2.6235)	0.71***
Adjusted $R^2 = 0.5668$		

only minor discounts will be given on routes characterised by a high level of demand, because more frequent flights are provided.

A negative coefficient is also given for the percentage of fully booked flights, though its level of significance is very low.

The degree of importance of the departure airport is directly correlated to parameter β, which means that if Ryanair plays a dominant role in the departure airport, average prices are lower, and significant discounts are more likely on tickets purchased in advance.

The variable representing the number of competitors operating on the same route is positive, and bears a high level of significance. This means that fierce direct competitiveness on the same route does not lead to a decrease in average ticket prices, but rather induces Ryanair to grant greater discounts on advance bookings. The next section of the empirical analysis examines the determinants of one variable that has already been analysed in the previous regressions, namely the percentage of fully booked flights.

The results of the relative regression analysis are shown in Table 6 (only explanatory variables which have registered a higher level of significance have been listed). Generally, short-haul routes from dominated airports present a higher percentage of fully booked flights. Also the GDPs of the areas linked with the airports contribute to an increase in the percentage of fully booked flights. All the analyses of variables were based on the optimum price function defined by Eq. (9), which has been drawn by considering an exponential demand curve with respect to price and advance purchasing time, as shown in Eq. (6). In the event that prices do not vary over time, the utility of potential customers tends to diminish, as tickets are booked well ahead of departure date. The relative optimal price function is thus steady, and does not decrease as the date of flight approaches. This does not mean that special fares are not likely to be offered on specific routes. As a matter of fact, when the number of bookings does not meet expectations, the carrier is more likely to reduce prices in order to encourage people to book tickets, aiming to maintain Ryanair's flight-filling strategy. Yet, the effects correlated to demand variability do not seem, on average, to affect the price trend, consequently a downward course is unlikely.

The unlikelyhood of a downward course seems however to clash with some of the price trends observed on a number of Ryanair's routes. Fig. 11 shows the average price for the Rome Ciampino–Shannon route, where it clearly reaches its lowest level between 50 and 60 days before the date of flight. A similar trend has also been recorded on other routes, although the downward trend observed as the date of flight approaches is not clear-cut and does not affect the average upward price trend that is typical of the last month before the scheduled departure.

In order to improve the statistical model, we used a demand curve equation with a different dependence with respect to advance booking, which led to the optimal price shown in Eq. (10). This kind of formulation presents a higher level of generality with respect to the previous analyses, and can be specifically obtained when coefficients γ and θ equal zero. Hypothesising that prices are not subject to variation, from the previous assumption it may be inferred that the utility of potential customers does not present a steady increase as the date of flight approaches. In other words, we admit to the possible existence of an optimal point in time when tickets are offered at a minimum price, as shown in Eq. (10).

This new model was tested on all the routes analysed earlier in order to verify the actual improvement of price estimations. This has been confirmed by the results, especially in the period between 60 and 90 days before the date of flight. In particular, the new estimates indicated that in 391 routes out of 550, the optimal purchasing period during which prices are at their lowest falls within 90 days from the scheduled departure date. Fig. 12 shows the distribution of the optimal purchasing periods for the 391 routes. On average, the optimal purchasing period occurs between 50 and 70 days before the date of flight, as shown below.

Table 6
Determinants of the percentage of fully booked flights on single routes.

Variable	Coefficient (std error)	Statistic T
Length	-0.03×10^{-03} (7.810×10^{-03})	−3.49***
Route frequency	0.25×10^{-03} (0.0003)	0.68***
Ryanair ASK/departure ASK	0.062 (0.0253)	2.46***
Ryanair ASK/destination ASK	0.015 (0.0238)	0.65***
Overall taxation	0.92×10^{-03} (0.829×10^{-03})	1.11***
Departure GDP	5.07×10^{-06} (1.72×10^{-06})	2.94***
Destination GDP	8.30×10^{-06} (1.71×10^{-06})	4.88***
Total number of competitors	0.006 (0.0039)	1.55***
Constant	0.050 (0.0192)	2.60***
Adjusted $R^2 = 0.1441$		

Table 5
Determinants of the dynamic pricing level (β coefficient).

Variable	Coefficient (std error)	Statistic T
Length	-0.22×10^{-03} (0.016×10^{-03})	−13.50***
Route frequency	-0.15×10^{-03} (0.0007)	−2.04***
Ryanair ASK/departure ASK	0.111 (0.0524)	2.13***
Ryanair ASK/destination ASK	0.042 (0.0490)	0.86***
Overall taxation	3.26×10^{-03} (0.0017)	1.91***
Departure GDP	1.65×10^{-06} (4.040×10^{-06})	0.41***
Destination GDP	2.95×10^{-06} (4.088×10^{-06})	0.72***
% Of fully booked flights	−0.078 (0.1142)	−0.69***
Departure population density	-0.01×10^{-03} (0.012×10^{-03})	−0.81***
Destination population density	-0.01×10^{-03} (0.012×10^{-03})	−0.99***
Total number of competitors	0.016 (0.0082)	2.03***
Constant	0.326 (0.0400)	8.17***
Adjusted $R^2 = 0.3756$		

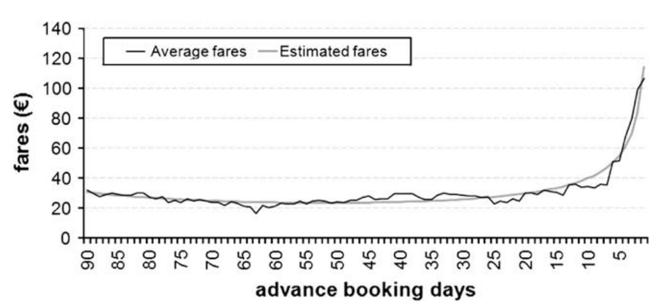

Fig. 11. Comparison between the daily average price and the estimated price for the Rome Ciampino–Shannon route.

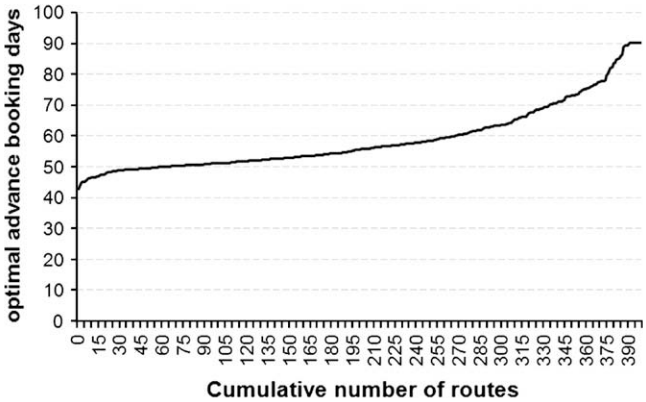

Fig. 12. Distribution of the optimal purchasing periods of time for 391 routes.

6. Conclusions and future developments

This work has provided an in-depth analysis of the pricing strategies of low-cost carriers. We focus on the features of the demand curve, hypothesising Ryanair's ability to maximise its profits. The price equation is obtained from an exponential demand function subject to Ryanair's profit maximisation, and shows that, as the date of flight approaches, the price trend tends to resemble a hyperbola. The empirical analysis is based on an original database of Ryanair's fares, made available on Ryanair's website, for each individual route operated during the year starting the 1st July, 2005. We estimate the price trends for each individual route over the 3 months prior departure, in terms of the average fares and the dynamic pricing intensity.

In general dynamic pricing intensity is strong in almost all the flights. However the phenomena is complex in terms of determinants.

We find positive correlation between fares and route length, route frequency and the percentage of fully booked flights. Length and route frequency are also significant variables with negative correlation to the dynamic pricing intensity. Ryanair grants fewer discounts on long haul and high-frequency routes, despite advance purchase.

We find a negative correlation between the Ryanair's importance in the departure and arrival airports and offered fares. The offer of the discounted fares appears as an incentive to use secondary airports. However, if Ryanair plays a dominant role in the departure airport, not only average prices are lower, but also significant discounts are more likely on tickets purchased in advance. This indicates the importance for the carrier to fulfil its capacity.

Surprisingly, the presence of competitors does not seem to heavily impact the average price. However, the variable representing the number of competitors operating on the same route is positively correlated to the dynamic pricing intensity. This means that direct competition on the same route does not lead to a decrease in average ticket prices, but rather induces Ryanair to grant greater discounts on advance bookings.

While this paper represents a first step in this direction, other factors should be analysed still in-depth, such as the temporal setting of the flight (namely time of day and day of the week). For instance, an improved measurement of the competitive pressure can be made through the analysis of the fares applied by Ryanair's competitors. We leave it for future research.

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